AMENDMENTS TO THE CLAIMS

This listing of claims will replace all prior versions, and listings, of claims in the application.

Listing of Claims:

Claim 1 (currently amended): A method of computer data analysis using neural networks, the method including:

generating a data representation using a data set, the data set including a plurality of attributes, wherein generating the data representation includes:

modifying the data set using a training algorithm, wherein the training algorithm includes growing the data set; ~~and~~

performing convergence testing, wherein convergence testing checks for convergence of the training algorithm~~,~~; and ~~wherein~~

repeating the modification~~ying~~ of the data set ~~is repeated~~ until convergence of the training algorithm occurs; and

displaying one or more subsets of the data set using the data representation.

Claim 2 (currently amended): ~~A~~ The method according to claim 1, further including generating the data set using input data, ~~and~~ wherein generating the data set includes formatting the input data, and initializing the formatted input data.

Claim 3 (currently amended): ~~A~~ The method according to claim 2, wherein formatting the input data further includes creating a container class including a list of data vectors, $\overline{\mathbf{D}}$, where $\mathbf{d}_i$ is the i th vector in $\overline{\mathbf{D}}$, and $\mathbf{d}_{i,j}$ is the j th element of vector i.

Claim 4 (currently amended): ~~A~~ The method according to claim 2, wherein formatting the input data further includes data scaling and binarisation of at least a portion of the data set.

Claim 5 (currently amended): ~~A~~ The method according to claim 4, wherein data scaling includes replacing each element in each data vector in the data set by a scaled representation of itself, where:

$\forall i \in [1, card(\mathbf{d})]$, $\forall \mathbf{d}_i \in \overline{\mathbf{D}}$; and

$$d_{i,j} = \left(d_{i,j} - i_{\min}\right) \Big/ \left(i_{\max} - i_{\min}\right).$$

Claim 6 (currently amended): ~~A~~ The method according to claim 4 ~~or 5~~, wherein binarisation includes converting attributes into one or more toggled attribute values.

Claim 7 (currently amended): ~~A~~ The method according to claim 1 ~~any one of the preceding claims~~, wherein performing convergence testing includes testing condition $q(t) < Q_e$.

Claim 8 (currently amended): ~~A~~ The method according to claim ~~any one of claims~~ 2 ~~to 7~~, wherein initializing the formatted input data includes:

calculating an autocorrelation matrix, $\aleph$ over the input data set $\overline{\mathbf{D}}$,

where $\aleph = \dfrac{1}{card(\overline{\mathbf{D}})} \sum_{\forall \mathbf{d} \in \overline{\mathbf{D}}} \mathbf{d} \cdot \mathbf{d}^T$;

finding two longest eigenvectors of $\aleph$, $\mathbf{e}_1$ and $\mathbf{e}_2$, where $|\mathbf{e}_1| > |\mathbf{e}_2|$; and

initializing vector values of each element of the data set F by spanning it with element values of the eigenvectors.

Claim 9 (currently amended): ~~A~~ The method according to claim 8, wherein initializing the vector values includes:

$$F_{<F_R,0>} := \mathbf{0}\underline{;}$$

$$F_{<F_R,F_C>} := \mathbf{e}_1\underline{;}$$

$$F_{<1,F_C>} := \mathbf{e}_1 + \mathbf{e}_2\underline{;}$$

$$F_{<F_R,F_C>} := \mathbf{e}_2\underline{;}$$

$$\forall c \in [2, F_C - 1],\ F_{<1,c>} := \frac{F_C}{F_C - c} F_{<1,F_C>} + \frac{F_C - c}{F_C} F_{<1,1>}\underline{;}$$

$$\forall c \in [2, F_C - 1],\ F_{<R_C,c>} := \frac{c}{F_C} F_{<F_R,F_C>} + \frac{F_C - c}{F_C} F_{<F_R,1>}\underline{;}$$

$$\forall r \in [2, F_R - 1],\ F_{<r,1>} := \frac{c}{F_R} F_{<F_R,1>} + \frac{F_R - r}{F_R} F_{<1,1>}\underline{;}$$

$$\forall r \in [2, F_R - 1],\ F_{<r,F_C>} := \frac{r}{F_R} F_{<F_R,F_C>} + \frac{F_R - r}{F_R} F_{<r,F_R>}\underline{;\text{ and}}$$

$$\forall r \in [2, F_R - 1],\ \forall c \in [2, F_C - 1],\ F_{<r,c>} := \frac{c}{F_C} F_{<r,F_C>} + \frac{F_C - c}{F_C} F_{<r,1>}.$$

Claim 10 (currently amended): ~~A~~ The method according to ~~any one of the preceding~~ claims 1, wherein the data set includes a plurality of data set nodes, and wherein growing the data set includes:

finding K_q for each of the data set nodes, where K_q is the node with the highest average quantization error, $\arg\max_q \{\overline{q}(t)_{K_q}\}$ for each of the data set nodes, where $\overline{q}(t)_{K_q} = \frac{1}{t-1}\sum_{t=1}^{t=t-1} q(t)_{K_q}$ is the average quantization error for node q, where:

$$K_x = \arg\max_x \{\|K_q - K_{<r(q)-1,c(q)>}\|, \|K_q - K_{<r(q)+1,c(q)>}\|\}$$

$$K_y = \arg\max_y \{\|K_q - K_{<r(q),c(q)-1>}\|, \|K_q - K_{<r(q),c(q)+1>}\|\}$$

if $\|K_y - K_c\| < \|K_x - K_c\|$ then

$n_r = r(y)$ if $r(y) < r(c)$, else $n_r = r(c)$; and

$n_c = c(y)$;

else $n_r = r(y)$; $n_c = c(x)$ if $c(x) < c(c)$, else $n_c = c(c)$;

inserting a new row and column after row n_r and column n_c; and

interpolating new attribute values for the newly inserted node vectors using: $K_{<r,n_c>} = (K_{<r,n_c-1>} + K_{<r,c_n+1>})\frac{\alpha}{2}$ and $K_{<n_r,c>} = (K_{<n_r-1,c>} + K_{<n_r+1,c>})\frac{\alpha}{2}$, where $\alpha \in U(0,1)$.

Claim 11 (currently amended): ~~A~~ The method according to ~~any one of the preceding~~ claims 1, wherein the training algorithm further includes:

$t = t + 1$;

$\forall \mathbf{d} \in \overline{\mathbf{D}}$;

if ($t < 50$ or $afterGrow$)

$$_{\mathbf{d}} = \underset{<r,c>, \forall r \in [1, F_R], \forall c \in [1, F_C]}{\arg\min} \left\| \mathbf{d} - F_{<r,c>} \right\|_{\rho}$$

$afterGrow = false$

else

$$_{\mathbf{d}} = FindSCWS(\mathbf{d})$$

call function: $FindNeighborhoodPatterns(\overline{\wp})$

call function: $BatchUpdateMatchVectors$

$$q(t) = \frac{1}{card(\overline{\mathbf{D}})} \sum_{i} \left(\left\| \mathbf{d} - F_{\wp \mathbf{d}} \right\| \rho \right);$$ and

if ($MayGrow(t)$ and $t < t_{\max}$), call function: $GrowKF$.

Claim 12 (currently amended): ~~A~~ The method according ~~to any one of the preceding~~ claims 1, wherein displaying one or more subsets of the data set includes:

using a composite view to view multiple attributes~~,~~ ; and ~~wherein~~

creating an additional attribute image ~~is created~~, wherein the additional attribute image displays~~ing~~ a union of a selected set of attributes.

Claim 13 (currently amended): ~~A~~ The method according to claim 12, wherein using a composite view further includes:

constructing an attribute matrix; and

selecting a highest value for each attribute value from the selected set of attributes.

Claim 14 (currently amended): ~~A~~ The method according to ~~any one of the preceding~~ claims 1, wherein displaying one or more subsets of the data set includes usinges a range filter, wherein using the range filter includes:

~~to~~ selecting regions on the data representation; and

filtering out nodes based on defined value ranges.

Claim 15 (currently amended): ~~A~~ The method according to ~~any one of the preceding~~ claims 1, wherein displaying one or more subsets of the data set includes using a zooming function, wherein using the zooming function includes:

making a selection of nodes to form a base reference of interest;

defining a set of data records from a second data set;

matching the second data set to the data representation;

flagging all records that are linked to the matched region; and

generating a second data representation using the flagged records.

Claim 16 (currently amended): ~~A~~ The method according to ~~any one of the preceding~~ claims 1, wherein displaying one or more subsets of the data set includes:

using visual scaling,;

changing the minimum and maximum values used to calculate a color progression used to visualize at least one of the plurality of attributes,; and

re-interpolating the active color ranges over the new valid range of attribute values.

Claim 17 (currently amended): ~~A~~ The method according to ~~any one of the preceding~~ claims 1, wherein displaying one or more subsets of the data set includes using a labeling engine, wherein using the labeling engine includes ~~to~~:

linking attribute columns in an input file to attributes in the data representation;

selecting attributes from the input file to be used for labelling;

determining with which row and column each row in the input file is associated; and

placing labels on the data representation.

Claim 18 (currently amended): ~~A~~ The method according to ~~anyone of the preceding~~ claims 1, wherein displaying one or more subsets of the data set includes using an advanced search function, wherein using the advanced search function includes ~~to~~:

reading a set of data records from a data source;

matching attribute columns from the set of data records to attributes in the data representation; and

displaying a list of all records that are associated with nodes that are part of the active selection on the data representation.

Claim 19 (currently amended): ~~A~~ The method according to ~~any one of the preceding~~ claims 1, wherein displaying one or more subsets of the data set includes using equal distance averaging (EDA), wherein using the equal distance averaging includes:

finding the node vector, $\mathbf{n}$, in the data representation that most closely represents the input data vector, $\mathbf{d}$, ~~:~~ where $\mathbf{n} = \arg\min_{K_{<r,c>}} \left\{ \left\| K_{<r,c>} - \mathbf{d} \right\|_p \right\}, \ \forall r \in [1, K_R], \forall c \in [1, K_C]$; and

replacing missing entries in $\mathbf{d}$ with the corresponding entries from $\mathbf{n}$.

Claim 20 (currently amended): ~~A~~ The method according to claim 19, wherein using the equal distance averaging further includes:

building a list of the data representation nodes values, $\overline{\mathbf{M}}$, such that for each element $\mathbf{m}$ of $\overline{\mathbf{M}}$, $\|\mathbf{m}-\mathbf{d}\|_{p}=0$; wherein if $\overline{\mathbf{M}}$ is empty, then replace each missing entry in $\mathbf{d}$ with corresponding entries in $\mathbf{n}$; and ~~I~~if $\overline{\mathbf{M}}$ is not empty, then replace each missing entry in $\mathbf{d}$ with the average value of the corresponding position of all the elements in $\overline{\mathbf{M}}$.

Claim 21 (currently amended): ~~A~~ The method according to ~~any one of the preceding~~ claims 1, wherein the data representation is a knowledge filter.

Claim 22 (currently amended): A method of computer data analysis using neural networks, the method including:

generating a data set, $\overline{\mathbf{D}}$, the data set including a plurality of attributes and a plurality of data set nodes;

initializing the data set, wherein initializing the data set includes~~ing~~:

calculating an autocorrelation matrix, $\aleph$ over the input data set $\overline{\mathbf{D}}$, where $\aleph = \frac{1}{card(\overline{\mathbf{D}})} \sum_{\forall \mathbf{d} \in \overline{\mathbf{D}}} \mathbf{d} \cdot \mathbf{d}^T$;

finding two longest eigenvectors of $\aleph$, $\mathbf{e}_1$ and $\mathbf{e}_2$, where $|\mathbf{e}_1| > |\mathbf{e}_2|$; and

initializing vector values of each element of a data representation F by spanning it with element values of the eigenvectors;

generating a data representation using a training algorithm, wherein the training algorithm includes growing the data set, and wherein growing the data set includes~~ing~~:

finding K_q for each of the data set nodes, where K_q is the node with the highest average quantization error, $\arg\max_q \{\overline{q}(t)_{K_q}\}$ for each of the data set nodes, where $\overline{q}(t)_{K_q} = \frac{1}{t-1}\sum_{t=1}^{t=t-1} q(t)_{K_q}$ is the average quantization error for node q, where:

$$K_x = \arg\max_x \{\|K_q - K_{<r(q)-1,c(q)>}\|, \|K_q - K_{<r(q)+1,c(q)>}\|\}$$

$$K_y = \arg\max_y \{\|K_q - K_{<r(q),c(q)-1>}\|, \|K_q - K_{<r(q),c(q)+1>}\|\}$$

if $\|K_y - K_c\| < \|K_x - K_c\|$ then

$n_r = r(y)$ if $r(y) < r(c)$, else $n_r = r(c)$; and

$n_c = c(y)$;

else $n_r = r(y)$; $n_c = c(x)$ if $c(x) < c(c)$, else $n_c = c(c)$;

inserting a new row and column after row n_r and column n_c; and

interpolating~~e~~ new attribute values for the newly inserted node vectors using: $K_{<r,n_c>} = \left(K_{<r,n_c-1>} + K_{<r,c_n+1>}\right)\frac{\alpha}{2}$ and $K_{<n_r,c>} = \left(K_{<n_r-1,c>} + K_{<n_r+1,c>}\right)\frac{\alpha}{2}$, where $\alpha \in U(0,1)$;

performing convergence testing, wherein convergence testing checks for convergence of the training algorithm~~,~~ ; ~~and wherein~~

repeating the training algorithm ~~is repeated~~ until convergence of the training algorithm occurs; and

displaying one or more subsets of the data set using the data representation.

Claim 23 (currently amended): ~~A~~ The method according to claim 22, wherein initializing the vector values further includes:

$F_{<F_R,0>} := \mathbf{0}$;

$F_{<F_R,F_C>} := \mathbf{e}_1$;

$F_{<1,F_C>} := \mathbf{e}_1 + \mathbf{e}_2$;

$F_{<F_R,F_C>} := \mathbf{e}_2$;

$\forall c \in [2, F_C - 1]$, $F_{<1,c>} := \frac{F_C}{F_C - c} F_{<1,F_C>} + \frac{F_C - c}{F_C} F_{<1,1>}$;

$\forall c \in [2, F_C - 1]$, $F_{<R_C,c>} := \frac{c}{F_C} F_{<F_R,F_C>} + \frac{F_C - c}{F_C} F_{<F_R,1>}$;

$\forall r \in [2, F_R - 1]$, $F_{<r,1>} := \frac{c}{F_R} F_{<F_R,1>} + \frac{F_R - r}{F_R} F_{<1,1>}$;

$\forall r \in [2, F_R - 1]$, $F_{<r,F_C>} := \frac{r}{F_R} F_{<F_R,F_C>} + \frac{F_R - r}{F_R} F_{<r,F_R>}$; and

$\forall r \in [2, F_R - 1]$, $\forall c \in [2, F_C - 1]$, $F_{<r,c>} := \frac{c}{F_C} F_{<r,F_C>} + \frac{F_C - c}{F_C} F_{<r,1>}$.

Claim 24 (currently amended): ~~A~~ The method according to claim 22 ~~or 23~~, wherein the training algorithm further includes:

$t = t + 1$;

$\forall \mathbf{d} \in \overline{\mathbf{D}}$;

if ($t < 50$ or $afterGrow$)

$$_{\mathbf{d}} = \underset{<r,c>, \forall r \in [1, F_R], \forall c \in [1, F_C]}{\arg\min} \left\| \mathbf{d} - F_{<r,c>} \right\|_{\rho}$$

$afterGrow = false$

else

$$_{\mathbf{d}} = FindSCWS(\mathbf{d})$$

call function: $FindNeighborhoodPatterns(\overline{\wp})$

call function: $BatchUpdateMatchVectors$

$$q(t) = \frac{1}{card(\overline{\mathbf{D}})} \sum_i \left(\left\| \mathbf{d} - F_{\wp \mathbf{d}} \right\| \rho \right)$$ ~~.~~; and

if ($MayGrow(t)$ and $t < t_{\max}$), call function: $GrowKF$.

Claim 25 (currently amended): ~~A~~ The method according to claim 22, ~~23, or 24,~~ wherein performing convergence testing includes testing condition $q(t) < Q_e$.

Claim 26 (currently amended): ~~A~~ The method according to ~~any one of~~ claims 22 ~~to 25~~, wherein displaying one or more subsets of the data set includes:

using a composite view to view multiple attributes~~,~~; and ~~wherein~~

creating an additional attribute image ~~is created~~, wherein the additional attribute image displays~~ing~~ a union of a selected set of attributes.

Claim 27 (currently amended): ~~A~~ The method according to claim 26, wherein using a composite view further includes:

constructing an attribute matrix; and

selecting a highest value for each attribute value from the selected set of attributes.

Claim 28 (currently amended): ~~A~~ The method according to ~~any one of~~ claim~~s~~ 22 ~~to 27~~, wherein displaying one or more subsets of the data set includes using~~es~~ a range filter, wherein using the range filter includes:

~~to~~ selecting regions on the data representation; and

filtering out nodes based on defined value ranges.

Claim 29 (currently amended): ~~A~~ The method according to ~~any one of~~ claim~~s~~ 22 ~~to 28~~, wherein displaying one or more subsets of the data set includes using a zooming function, wherein using the zooming function includes:

making a selection of nodes to form a base reference of interest;

defining a set of data records from a second data set;

matching the second data set to the data representation;

flagging all records that are linked to the matched region; and

generating a second data representation using the flagged records.

Claim 30 (currently amended): ~~A~~ The method according to ~~any one of~~ claim~~s~~ 22 ~~to 29~~, wherein displaying one or more subsets of the data set includes:

using visual scaling~~,~~;

changing the minimum and maximum values used to calculate a color progression used to visualize at least one of the plurality of attributes~~,~~; and

re-interpolating the active color ranges over the new valid range of attribute values.

Claim 31 (currently amended): ~~A~~ The method according to ~~any one of~~ claims 22 ~~to 30~~, wherein displaying one or more subsets of the data set includes using a labeling engine, wherein using the labeling engine includes ~~to~~:

linking attribute columns in an input file to attributes in the data representation;

selecting attributes from the input file to be used for label~~l~~ing;

determining with which row and column each row in the input file is associated; and

placing labels on the data representation.

Claim 32 (currently amended): ~~A~~ The method according to ~~any one of~~ claims 22 ~~to 31~~, wherein displaying one or more subsets of the data set includes using an advanced search function, wherein using the advanced search function includes ~~to~~:

reading a set of data records from a data source;

matching attribute columns from the set of data records to attributes in the data representation; and

displaying a list of all records that are associated with nodes that are part of the active selection on the data representation.

Claim 33 (currently amended): ~~A~~ The method according to ~~any one of~~ claims 22 ~~to 32~~, wherein displaying one or more subsets of the data set includes using equal distance averaging (EDA), wherein using the equal distance averaging includes:

finding the node vector, $\mathbf{n}$, in the data representation that most closely represents the input data vector, $\mathbf{d}$, ~~:~~ where $\mathbf{n} = \arg\min_{K_{<r,c>}} \left\{ \| K_{<r,c>} - \mathbf{d} \|_{p} \right\}, \; \forall r \in [1, K_R], \forall c \in [1, K_C]$; and

replacing missing entries in $\mathbf{d}$ with the corresponding entries from $\mathbf{n}$.

Claim 34 (currently amended): ~~A~~ The method according to claim 33, wherein using the equal distance averaging further includes:

building a list of the data representation nodes values, $\overline{\mathbf{M}}$, such that for each element $\mathbf{m}$ of $\overline{\mathbf{M}}$, $\|\mathbf{m}-\mathbf{d}\|_{\rho}=0$; wherein if $\overline{\mathbf{M}}$ is empty, then replace each missing entry in $\mathbf{d}$ with corresponding entries in $\mathbf{n}$; and ~~I~~if $\overline{\mathbf{M}}$ is not empty, then replace each missing entry in $\mathbf{d}$ with the average value of the corresponding position of all the elements in $\overline{\mathbf{M}}$.

Claim 35 (currently amended): ~~A~~ The method according to ~~any one of~~ claims 22 ~~to 34~~, wherein the data representation is a knowledge filter.

Claim 36 (currently amended): ~~A~~ The method according to any of the preceding claims wherein the data representation includes a latent model of the data set.

Claim 37 (currently amended): A system for performing data analysis using neural networks, the system including:

~~one or more~~ a processor~~s~~;

~~one or more~~ a memory~~ies~~ coupled to the one or more processors; and

program instructions stored in the ~~one or more~~ memory~~ies~~, the ~~one or more~~ processor~~s~~ being operable to execute the program instructions, wherein the program instructions include~~ing~~ processor executable code for executing the steps of:

generating a data representation using a data set, the data set including a plurality of attributes, wherein generating the data representation includes:

modifying the data set using a training algorithm, wherein the training algorithm includes growing the data set; and

performing convergence testing, wherein convergence testing checks for convergence of the training algorithm~~,~~; and ~~wherein~~

repeating the modification~~ying~~ of the data set ~~is repeated~~ until convergence of the training algorithm occurs; and

displaying one or more subsets of the data set using the data representation.

Claim 38 (currently amended): ~~A~~ The system according to claim 37, wherein performing convergence testing includes testing condition $q(t) < Q_e$.

Claim 39 (currently amended): ~~A~~ The system according to claim 37 ~~or 38~~, wherein the data set includes a plurality of data set nodes, and wherein growing the data set includes:

finding K_q for each of the data set nodes, where K_q is the node with the highest average quantization error, $\arg\max_q \left\{ \overline{q}(t)_{K_q} \right\}$ for each of the data set nodes, where $\overline{q}(t)_{K_q} = \frac{1}{t-1} \sum_{t=1}^{t=t-1} q(t)_{K_q}$ is the average quantization error for node q, where:

$$K_x = \arg\max_x \left\{ \left\| K_q - K_{<r(q)-1,c(q)>} \right\|, \left\| K_q - K_{<r(q)+1,c(q)>} \right\| \right\}$$

$$K_y = \arg\max_y \left\{ \left\| K_q - K_{<r(q),c(q)-1>} \right\|, \left\| K_q - K_{<r(q),c(q)+1>} \right\| \right\}$$

if $\left\| K_y - K_c \right\| < \left\| K_x - K_c \right\|$ then

$n_r = r(y)$ if $r(y) < r(c)$, else $n_r = r(c)$; and

$n_c = c(y)$;

else $n_r = r(y)$; $n_c = c(x)$ if $c(x) < c(c)$, else $n_c = c(c)$;

inserting a new row and column after row n_r and column n_c; and

interpolating new attribute values for the newly inserted node vectors using: $K_{<r,n_c>} = \left(K_{<r,n_c-1>} + K_{<r,c_n+1>} \right) \frac{\alpha}{2}$ and $K_{<n_r,c>} = \left(K_{<n_r-1,c>} + K_{<n_r+1,c>} \right) \frac{\alpha}{2}$, where $\alpha \in U(0,1)$.

Claim 40 (currently amended): ~~A~~ The system according to claim 37~~, 38, or 39,~~ wherein the training algorithm further includes:

$t = t + 1$;

$\forall \mathbf{d} \in \overline{\mathbf{D}}$;

if ($t < 50$ or *afterGrow*)

$$_{\mathbf{d}} = \underset{<r,c>, \forall r \in [1, F_R], \forall c \in [1, F_C]}{\arg\min} \left\| \mathbf{d} - F_{<r,c>} \right\|_{\rho}$$

$afterGrow = false$

else

$$_{\mathbf{d}} = FindSCWS(\mathbf{d})$$

call function: $FindNeighborhoodPatterns(\overline{\wp})$

call function: $BatchUpdateMatchVectors$

$$q(t) = \frac{1}{card(\overline{\mathbf{D}})} \sum_i \left(\left\| \mathbf{d} - F_{\wp \mathbf{d}} \right\| \rho \right);$$ and

if ($MayGrow(t)$ and $t < t_{\max}$), call function: $GrowKF$.

Claim 41 (currently amended): ~~A~~ The system according to ~~any one of~~ claims 37 ~~to 40~~, wherein the program instructions ~~further include~~ for displaying one or more subsets of the data set further includes processor executable code for executing the steps of:

using a composite view to view multiple attributes~~,~~; and ~~wherein~~

creating an additional attribute image ~~is created~~, wherein the additional attribute image displays~~ing~~ a union of a selected set of attributes.

Claim 42 (currently amended): ~~A~~ The system according to ~~any one of~~ claims 37 ~~to 41~~, wherein the program instructions further include processor executable code for executing the steps of:

constructing an attribute matrix; and

selecting a highest value for each attribute value from the selected set of attributes.

Claim 43 (currently amended): ~~A~~ The system according to ~~any one of~~ claims 37 ~~to 42~~, wherein displaying one or more subsets of the data set includes usinges a range filter, ~~to~~ wherein the program instructions further include processor executable code for executing the steps of:

selecting regions on the data representation; and

filtering out nodes based on defined value ranges.

Claim 44 (currently amended): ~~A~~ The system according to ~~any one of~~ claims 37 ~~to 43~~, wherein displaying one or more subsets of the data set includes using a zooming function, wherein the ~~wherein the~~ program instructions further include processor executable code for executing the steps of:

making a selection of nodes to form a base reference of interest;

defining a set of data records from a second data set;

matching the second data set to the data representation;

flagging all records that are linked to the matched region; and

generating a second data representation using the flagged records.

Claim 45 (currently amended): ~~A~~ The system according to ~~any one of~~ claims 37 ~~to 44~~, wherein displaying one or more subsets of the data set includes using visual scaling, wherein the ~~wherein the~~ program instructions further include processor executable code for executing the steps of:

changing the minimum and maximum values used to calculate a color progression used to visualize at least one of the plurality of attributes; and

re-interpolating the active color ranges over the new valid range of attribute values.

Claim 46 (currently amended): ~~A~~ The system according to ~~any one of~~ claims 37 ~~to 45~~, wherein displaying one or more subsets of the data set includes using a labeling engine, wherein the program instructions further include processor executable code for executing the steps of:

linking attribute columns in an input file to attributes in the data representation;

selecting attributes from the input file to be used for labelling;

determining with which row and column each row in the input file is associated; and

placing labels on the data representation.

Claim 47 (currently amended): ~~A~~ The system according to ~~any one of~~ claims 37 ~~to 46~~, wherein displaying one or more subsets of the data set includes using an advanced search engine, wherein the program instructions further include processor executable code for executing the steps of:

~~displaying one or more subsets of the data set includes using an advanced search function to:~~

reading a set of data records from a data source;

matching attribute columns from the set of data records to attributes in the data representation; and

displaying a list of all records that are associated with nodes that are part of the active selection on the data representation.

Claim 48 (currently amended): ~~A~~ The system according to ~~any one of~~ claims 37 ~~to 47~~, wherein displaying one or more subsets of the data set includes using equal distance averaging (EDA), wherein the program instructions further include processor executable code for executing the steps of:

finding the node vector, $\mathbf{n}$, in the data representation that most closely represents the input data vector, $\mathbf{d}$,~~:~~ where $\mathbf{n} = \arg\min_{K_{<r,c>}} \left\{ \left\| K_{<r,c>} - \mathbf{d} \right\|_{\rho} \right\}, \ \forall r \in [1, K_R], \forall c \in [1, K_C]$;

and

replacing missing entries in $\mathbf{d}$ with the corresponding entries from $\mathbf{n}$.

Claim 49 (currently amended): ~~A~~ The system according to claim 48, wherein the program instructions further include~~s~~ processor executable code for executing the steps of:

building a list of the data representation nodes values, $\overline{\mathbf{M}}$, such that for each element $\mathbf{m}$ of $\overline{\mathbf{M}}$, $\left\| \mathbf{m} - \mathbf{d} \right\|_{\rho} = 0$; wherein if $\overline{\mathbf{M}}$ is empty, then replace each missing entry in $\mathbf{d}$ with corresponding entries in $\mathbf{n}$; and ~~I~~if $\overline{\mathbf{M}}$ is not empty, then replace each missing entry in $\mathbf{d}$ with the average value of the corresponding position of all the elements in $\overline{\mathbf{M}}$.

Claim 50 (currently amended): ~~A~~ The system according to ~~any one of~~ claims 37 ~~to 49~~, wherein the data representation is a knowledge filter.

Claim 51 (currently amended): ~~A~~ The system according to ~~any one of~~ claims 37 ~~to 50~~, wherein the data representation includes a latent model of the data set.

Claim 52 (currently amended): A computer program product for computer data analysis using neural networks, the computer program product including:

computer-readable program code for generating a data representation using a data set, the data set including a plurality of attributes, wherein generating the data representation includes:

modifying the data set using a training algorithm, wherein the training algorithm includes growing the data set; ~~and~~

performing convergence testing, wherein convergence testing checks for convergence of the training algorithm~~,~~; and ~~wherein~~

repeating the training algorithm ~~is repeated~~ until convergence of the training algorithm occurs; and

computer-readable program code for displaying one or more subsets of the data set using the data representation.

Claim 53 (currently amended): ~~A~~ The computer program product according to claim 52, wherein the data set includes a plurality of data set nodes, and the computer program product further including computer-readable program code for growing the data set including:

finding K_q for each of the data set nodes, where K_q is the node with the highest average quantization error, $\arg\max_q \{\overline{q}(t)_{K_q}\}$ for each of the data set nodes, where $\overline{q}(t)_{K_q} = \frac{1}{t-1}\sum_{t=1}^{t=t-1} q(t)_{K_q}$ is the average quantization error for node q, where:

$$K_x = \arg\max_x \{\|K_q - K_{<r(q)-1,c(q)>}\|, \|K_q - K_{<r(q)+1,c(q)>}\|\}$$

$$K_y = \arg\max_y \{\|K_q - K_{<r(q),c(q)-1>}\|, \|K_q - K_{<r(q),c(q)+1>}\|\}$$

if $\|K_y - K_c\| < \|K_x - K_c\|$ then

$n_r = r(y)$ if $r(y) < r(c)$, else $n_r = r(c)$; and

$n_c = c(y)$;

else $n_r = r(y)$; $n_c = c(x)$ if $c(x) < c(c)$, else $n_c = c(c)$;

inserting a new row and column after row n_r and column n_c; and

interpolating new attribute values for the newly inserted node vectors using: $K_{<r,n_c>} = (K_{<r,n_c-1>} + K_{<r,c_n+1>})\frac{\alpha}{2}$ and $K_{<n_r,c>} = (K_{<n_r-1,c>} + K_{<n_r+1,c>})\frac{\alpha}{2}$, where $\alpha \in U(0,1)$.

Claim 54 (currently amended): ~~A~~ The computer program product according to claim 52 ~~or 53~~, wherein the data representation includes a latent model of the data set.

Claim 55 (currently amended): An apparatus for performing data analysis using neural networks, the apparatus including:

means for representing a data set, the data set including a plurality of attributes;

means for generating the representation means using the data set, wherein generating the representation means includes:

modifying the data set using a training algorithm, wherein the training algorithm includes growing the data set; ~~and~~

performing convergence testing, wherein convergence testing checks for convergence of the training algorithm~~,~~; and ~~wherein~~

repeating the modificationy~~ing~~ of the data set ~~is repeated~~ until convergence of the training algorithm occurs; and

means for displaying one or more subsets of the data set using the modified data representation.

Claim 56 (currently amended): ~~An~~ The apparatus according to claim 55, wherein the representation means includes a latent model of the data set.

Claim 57 (withdrawn): A method of computer data analysis using neural networks substantially as herein described with reference to the accompanying drawings.

Claim 58 (withdrawn): A system for performing data analysis using neural networks substantially as herein described with reference to the accompanying drawings.

Claim 59 (withdrawn): A computer program product for computer data analysis using neural networks substantially as herein described with reference to the accompanying drawings.

Claim 60 (withdrawn): An apparatus for performing data analysis using neural networks substantially as herein described with reference to the accompanying drawings.